

Human Heuristics for Autonomous Agents

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Abstract. We investigate the problem of autonomous agents processing pieces of information that may be corrupted (tainted). Agents have the option of contacting a central database for a reliable check of the status of the message, but this procedure is costly and therefore should be used with parsimony. Agents have to evaluate the risk of being infected, and decide if and when communicating partners are affordable. Trustability is implemented as a personal (one-to-one) record of past contacts among agents, and as a mean-field monitoring of the level of message corruption. Moreover, this information is slowly forgotten in time, so that at the end everybody is checked against the database. We explore the behavior of a homogeneous system in the case of a fixed pool of spreaders of corrupted messages, and in the case of spontaneous appearance of corrupted messages.

1 Introduction

One of the most promising area in computer science is the design of algorithms and computer architectures closely based on our reasoning process and on how the brain works. Human neural circuits receive, encode and analyze the “available information” from the environment in a fast, reliable and economical way. The evolution of human cognition could be viewed as the result of a continuous improvement of neural structures which drive the decision making processes from the inputs to the final behaviors, cognitions and emotions. Heuristics are simple, efficient rules, hard-coded by evolutionary processes or learned, which have been proposed to explain how people make decisions, come to judgments, and solve problems, typically when facing complex problems or incomplete information. It is common experience that that much of human reasoning and decision making can be modeled by fast and frugal heuristics that make inferences with limited time and knowledge. For example, Darwin’s deliberation over whether to marry provides an interesting example of such heuristic process [1,2].

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Let us quickly review some widely accepted hypothesis about heuristics. In the early 1970s, Daniel Kahneman and Amos Tversky (K&T) produced a series of important papers about decisions under uncertainty [3,4,5,6,7]. Their basic claim was that in assessing probabilities, *“people rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations”*. Although K&T claimed that, as a general rule, heuristics are quite valuable, in some cases, their use leads *“to severe and systematic errors”*. One of the most striking features of their argument was that the errors follow certain statistics and, therefore, they could be described and even predicted. The resulting arguments have proved highly influential in many fields, including computer science (and particularly in human-machine interaction area) where the influence has stemmed from the effort to connect algorithmic accuracy to speed of elaboration and, equally important, to the algorithmic understanding of the human logic [7]. If human beings use identifiable heuristics, and if they are prone to systematic errors, we might be able to design computer architectures and algorithms to improve human-computer interaction (and also to study human behavior).

K&T described three general-purpose heuristics: **representativeness**, **availability** and **anchoring**. People use the *availability* heuristic when they answer a question of probability by relying upon knowledge that is readily available rather than examine other alternatives or procedures. There are situations in which people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind. For example, one may assess the risk of heart attack among middle-aged people by recalling such occurrences among one’s acquaintances. Availability is a useful clue for assessing frequency or probability, because instances of large classes are usually reached better and faster than instances of less frequent classes. However, availability is affected by factors other than frequency and probability. This is a point about how familiarity can affect the availability of instances. For people without statistical knowledge, it is far from irrational to use the availability heuristic; the problem is that this heuristic can lead to serious errors of fact, in the form of excessive fear of small risks and neglect of large ones.

The *representativeness* heuristic is involved when people make an assessment of the degree of correspondence between a sample and a population, an instance and a category, an act and an actor or, more generally, between an outcome and a model. This heuristic can be thought of as the reflexive tendency to assess the similarity of characteristics on relatively salient and even superficial features, and then to use these assessments of similarity as a basis of judgment. Representativeness is composed by categorization and generalization: in order to forecast the behavior of an (unknown) subject, we first identify the group to which it belongs (categorization) and then we associate the “typical” behavior of the group to the item. Suppose, for example, that the question is whether some person, Paul, is a computer scientists or a clerk employed in the public administration. If Paul is described as shy and withdrawn, and as having a passion for detail, most people will think that he is likely to be a computer scientist and

ignore the “base-rate”, that is, the fact that there far more clerk employed in public admin than computer scientists. It should be readily apparent that the representativeness heuristic will produce problems whenever people are ignoring base-rates, as they are prone to do.

K&T also suggested that estimates are often made from an initial value, or *anchoring*, which is then adjusted to produce a final answer. The initial value seems to have undue influence. In one study, K&T asked subjects to say whether the number that emerged from the wheel was higher or lower than the relevant percentage. It turned out that the starting point, though clearly random, greatly affected people’s answers. If the starting point was 65, the median estimate was 45%; if the starting point was 10, the median estimate was 25%.

Several of recent contributions on heuristic have put the attention on the “dual-process” to human thinking [8,9,10,11,12]. According to these hypothesis, people have two systems for making decisions. One of them is rapid, intuitive, but sometimes error-prone; the other is slower, reflective, and more statistical. One of the pervasive themes in this collection is that heuristics and biases can be connected with the intuitive system and that the slower, more reflective system might be able to make corrections. The dual-process idea has some links with the experimental evidences of the presence of areas for emotions in the brain, for instance of fear-type. These “emotional” areas may be triggered before than the cognitive areas become involved.

We shall try to consider some of these concepts to model autonomous agents that have the task of processing messages from sources that are not always trustable. The agent is a direct abstraction of an human being, easily understandable by psychologists and biologist with the advantage of following a stochastic dynamics that can be combined with other approaches like ODE [14,15,16,13,17]. Here we make the analogy between the diffusion of hoaxes, gossips, etc., and that of computer viruses or worms.

The incoming information may be corrupted for many reasons: some agents may be infected by malware and particularly viruses, some of them may be programmed to provide false information or they may just be malfunctioning. Let us suppose that the processing of a corrupted information will infect the elaborated message, so that the corruption “percolates and propagates” into the connection network, unless stopped. We assume that an agent may contact a central database for inquiring about the reliability of a message, but this checkout is costly, at least in terms of the time required for processing the information. Therefore, an agent is confronted with two opportunities: either trust the sender, accept the message and the risk or passing false information and process it in a short time, or contact the central database, be sure of the correctness of the message but also waste more time (or other resources such as bandwidth) in elaborating it. This is analogous to the passport check when crossing a boundary: customers may either trust the identity card and let people pass quickly, or check them against a database, slowing down the queue.

This paper, which is motivated by the fact that human heuristics may be used to improve the efficiency of artificial systems of autonomous decision-makers

agents, is structured as follows. In Section 2, we introduce a model where the above mentioned heuristics are implemented. Section 3 focuses on equilibrium and asymptotic conditions in the absence of infection. In Section 4, we describe the different scenarios which are considered (no infection, quenched infection and annealed infection); numerical results for different value of control parameters under infection are reported in Section 5. A discussion about the psychological implications of the model and conclusions are drawn in Section 6.

2 Model

Let us consider a scenario with N agents, identified by the index $i = 1, \dots, N$. Each agent interacts with other K randomly chosen agents. The connections indicate messages transferred. In principle, one can have input connections with himself (meaning further processing of a given piece of information) and multiple connections with a given partner (more information transferred). An agent receives information from its connecting inputs, elaborates it and send the result to its output links. Let us assume for simplicity that this occurs in a synchronous way and at discrete time steps t . The information however can be tainted (corrupted), either maliciously (virus, sabotage, attack) or because it is based on incorrect data.

If an information is tainted, and it is accepted for processing, it contaminates the output. All agents have the possibility of checking the correctness of the incoming messages against a central database, but this operation is costly (say, in terms of time), and therefore heuristics are used to balance between cost and the risk of being infected.

An agent i has a dynamical memory for the reliability of its partners j , $-1 \leq \alpha_{ij} \leq 1$; this memory is used to decide if a message is acceptable or not. The greater $\alpha_{ij} > 0$, the more the partner is considered reliable, the reverse for $\alpha_{ij} < 0$. However, the trusting on an individual is not an absolute value, it has to be compared with the perception of the level of the infection. Let us denote by $0 \leq A_i \leq 1$ the perception of the risk *i.e.*, the perceived probability of message contamination, of individual i . A simple yet meaningful way of combining risk perception with uncertainty is to assume that each individual i decides according with its previous knowledge (α_{ij}) if $|\alpha_{ij}| > A_i$ and checks against the database (*i.e.*, get to know the truth) otherwise. If A_i is large, the agent i will be suspicious and check many messages against the database, the reverse for small values of A_i .

After checking the database, one knows the truth about his/her partner. This information can be used to increase or decrease α_{ij} and also to compute A_i . In particular, if the check is positive (negative), α_{ij} increases (decreases) of a given amount v_α . Finally A_i is increased by a quantity $v_A n_i / c_i$, where c_i is the cost (total number of checks for a given time step) and n_i the number of infected discovered. The idea is that A_i represents the perceived “average” level of infection, corresponding to the “risk perception” of being infected. We shall limit here to fixed and homogeneous responses, in an more realistic case,

different classes of agents or individuals will react differently, according to their “programming” and their past experiences, to a given perception of the infection level.

Some of these quantities change smoothly in time. There is an oblivion mechanism on α_{ij} and A_i , implemented with the parameters r_α and r_A , respectively, such that the information stored τ time steps before the present time has weight $(1 - r)^\tau$. New information is stored with weight r . This mechanism emulates a finite memory of the agent, without the need of managing a list.

The observable quantities are the total number of infected individuals, I , the cost of querying the database, C and the number of errors E , which are given by the number of tainted accepted messages and not-tainted refused messages.

In this model, we are only interested in the correctness of the message, not in its content. Actually, a real message should be considered as a set of ‘atomic’ parts, each of which can be analyzed, eventually with their relations, in order to judge the reliability of the message itself. For instance, the spam detection mechanism is often based on a score assigned to patterns (*e.g.*, MONEY, SEX, LOTTERY) appearing in the message. Therefore, a more accurate model should represent messages as vectors or lists of items. We deal here with a simple scalar approximation.

We try to include the human heuristics in this simple model by means of A (representativeness) and α_{ij} (availability). The oblivion mechanism can moreover be considered the parameter corresponding to the “anchoring” experiences. In our present model, there is only one variable connected to affordability (from completely trustable to completely not trustable), and the categorization procedure consists essentially in trying to assess the placement of an individual on this axis. The trustability of an individual (α_{ij}) depends on the past interactions. Since A represents the average level of infectivity, the trustability of an individual is evaluated against it, in order to save the cost (or the time) of the check against the central database.

3 Relaxation to equilibrium and asymptotic state without infection

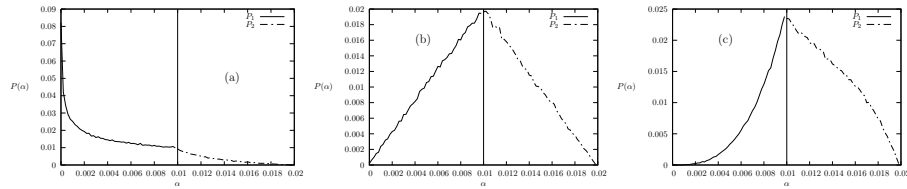


Fig. 1. The asymptotic distribution $P(\alpha)$ for $a < 2r$ ($a = 0.006$ and $r = 0.01$) (a); $a = 2r$ ($a = 0.01$ and $r = 0.005$) (b); $a > 2r$ ($a = 0.02$ and $r = 0.005$) (c).

In order to put into evidence the emerging features of our model, let us first study the case without infection. Without “stimulation”, the threshold A_i is fixed, and takes the value v_A for all individuals. The only dynamical variables are the α_{ij} .

Starting from a peaked (single-valued) distribution of α_{ij} , the model exhibits oscillatory patterns and long transients towards an equilibrium distribution (Fig. 1). We found that by increasing the connectivity K , the peaks become thinner and higher, following a linear relationship. The affinities α_{ij} in the asymptotic state have a non trivial distribution, ranging from 0 to $2v$. Let us call $P(\alpha)$ the probability distribution of α . From numerical simulation (see Fig. 1), one can see that $P(\alpha)$ can be divided into two branches, $P_1(\alpha)$ for $0 \leq \alpha \leq v$ and $P_2(\alpha)$ for $v \leq \alpha \leq 2v$. The evolution of $P(\alpha)$ is given by the combination of two phases: control against the database, that in the mean field approach occurs with probability $a = K/N$ for all $\alpha \leq v$ (and therefore for P_1), and the oblivion mechanism, that multiplies all α by $(1 - r_\alpha)$. Combining the two effects, one finds for the asymptotic state

$$P_1(\alpha) = \frac{1-a}{1-r_\alpha} P_1\left(\frac{\alpha}{1-r_\alpha}\right), \quad (1)$$

$$P_2(\alpha) = \frac{a}{1-r_\alpha} P_1\left(\frac{\alpha}{1-r_\alpha} - v\right) + \frac{1}{1-r_\alpha} P_2\left(\frac{\alpha}{1-r_\alpha}\right). \quad (2)$$

From Eq. (1), one gets easily that $P_1(\alpha) \propto \alpha^x$, with

$$x = \frac{\ln(1-a)}{\ln(1-r_\alpha)} - 1 \simeq \frac{a}{r_\alpha} - 1.$$

In particular, the value $x = 1$ (Fig. 1-b) corresponds to $a = 2r_\alpha$. We were not able to express the asymptotic distribution $P_2(\alpha)$ in terms of known functions.

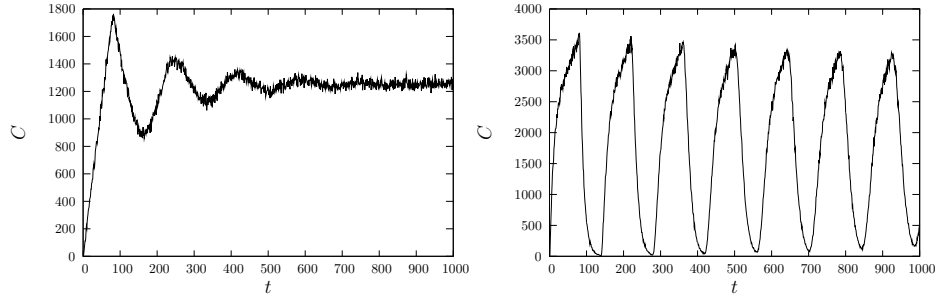


Fig. 2. Relaxation to equilibrium for the cost C for $N = 500$, $r_\alpha = 0.005$ and $K = 5$ ($a = 0.01$) (left); $K = 50$ ($a = 0.1$) (right).

The process of relaxation to the equilibrium is in general given by oscillations, whose period is related to r_α . A rough estimation can be obtained by considering

that a pulse of agents with the same value of $\alpha = 2v$ will experience the oblivion at an exponential rate $(1 - r_\alpha)^T$, until $\alpha = v$, after which a fraction a of the pulse is re-injected again to the value $\alpha = 2v$. The condition for the pseudo-periodicity (for the fraction a of agents) is

$$2v(1 - r_\alpha)^T = v,$$

from which the period T can be estimated

$$T \simeq -\frac{\ln(2)}{\ln(1 - r_\alpha)} \simeq \frac{\ln(2)}{r_\alpha}$$

in the limit of small r_α .

Since the re-injected fraction is given by a , the larger is its value, the larger the oscillations and the slower is the relaxation to the asymptotic distribution, as is shown in Fig. 2. One can notice that the period is roughly the same (same value of r_α), but the amplitude of oscillations is much larger in the plot to the right (larger a).

Since $a = K/N$, these large oscillations make difficult to perform measurements on the asymptotic state on small populations, but large values of N require longer simulations. One may say that the model is intrinsically complex.

The asymptotic cost is given by $C_\infty = a \int_0^{v_\alpha} P_1(\alpha) \propto av_\alpha^{a/r_\alpha}$. As one can see from Fig. 1, there is a cost even in the absence of infection, since the agents have to monitor the level of infection against the database. The lower values of the cost are associated to values of r_α smaller than a .

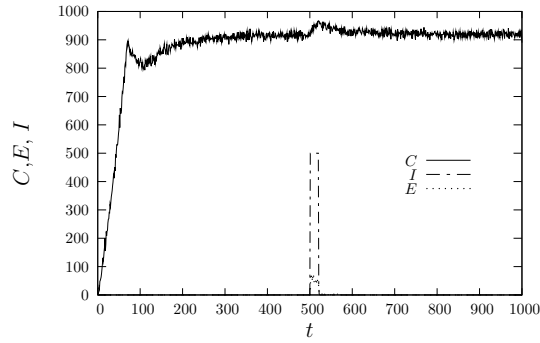


Fig. 3. Temporal behavior of the cost C , infection I and error level E for $K = 5$, $n = 500$ ($a = 0.01$), $r = 0.005$. The pulse is at the time 500

4 Infectivity scenarios

The source of infection may be quenched, *i.e.*, a fraction p of the population always emits tainted messages, or annealed, in which case the fraction p of the

spreaders is changed at each time step. Let us first study the case of a pulse of infection (with $p = 1$) in the asymptotic state and a duration $\Delta t = 20$. For large values of the asymptotic cost, The infection is removed in just a few time steps, as shown in Fig. 3.

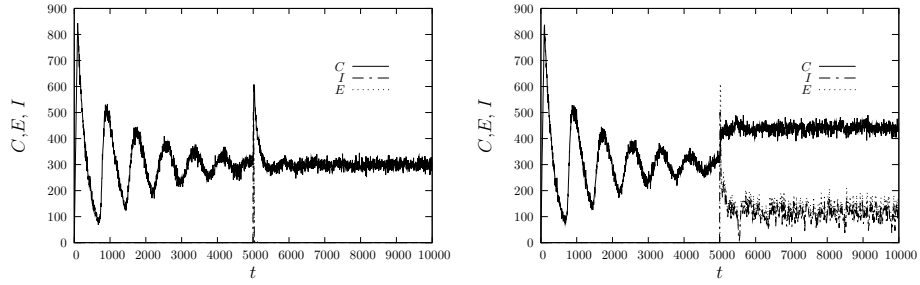


Fig. 4. Temporal behavior of the cost C , infection i and error level E for $K = 2$, $n = 500$ ($a = 0.004$), $r = 0.001$. Left: $v_A = 10^{-3}$ (eradication). Right: $v_A = 10^{-4}$ (endemic infection). The pulse occurs at time 5000

For smaller values of the cost, the fate of the infection is related to the scenario (quenched or annealed infectors). If the infection level is small, and the infectors are quenched, the rising of the corresponding α_{ij} efficiently isolate the contagion. In the case of a “pulse” of infection, or for annealed infectors, the fate of the contagion is mainly ruled by the quantity A_i . If A_i grows rapidly (v_A sufficiently large), a temporary increase of the cost is enough to eradicate the epidemics, see Fig. 4. In the opposite case, the infection becomes endemic even for non-persistent infectors: it is maintained by the spreading mechanism. The increment used in the following investigations is small enough so that we can observe the persistence of the infection.

If the infectors are persistently renewed, the contagion cannot get eradicated but only kept under control. The role of the two heuristics is different in the two cases.

The representativeness heuristic (α_{ij}) is the optimal strategy to detect agents which are constantly less reliable than the others (quenched case), but it is completely useless in the annealed case. The availability heuristic (A_i), considering at each time step the average infection of the system, is able to control the spread of infection in the annealed case.

The oblivion mechanism, related to the anchoring heuristic, is a the key parameter governing the speed of adaptation to variable external conditions. It controls the oscillations of the cost (Fig. 2) and it is fundamental to minimize the computational load of the control process. The oblivion of α_{ij} (representativeness parameter) controls the computational cost at the equilibrium in both cases. High values of r_α correspond to a conservative behavior of the system, in this case a large computational cost and a corresponding low number of infected

and errors characterized the equilibrium. Low values of r_α correspond to the dissipative behavior for which the system minimizes the computational cost but allows large fluctuations of infected and high values of errors.

5 Dynamical behavior

We run extensive numerical simulations and recorded the asymptotic cost C , number of infected people I , and errors E as function of the oblivion parameters (r_α and r_A), the probability and the pulse of infection (p), and the density of contacts (K). In these simulation we kept $v_A = 10^{-6}$ in order to stay in the endemic phase, and therefore r_A did not play any role.

Fig. 5 shows the effect of infection with different values of r_α and contact density for $K = 5$ and $N = 500$. Plots (a) and (b) show the oscillatory patterns without infection ($p = 0$) for $r_\alpha = 10^{-3}$ (a), $r_\alpha = 10^{-4}$ (b). The oblivion r_α (in the presence of infection) changes both the oscillatory frequency (as studies in the previous section) and the oscillatory delay before convergence to a basic fluctuation pattern. Note that increasing r_α the frequency of the oscillations increases. When $r_\alpha = 0.0001$, (a), the period T is $T = \ln 210^4 \approx 7000$; for $r_\alpha = 0.001$, (b), $T \approx 700$). By adding infection (annealed version), we obtain a quicker convergence the basal fluctuation equilibrium (c). We found that the time to reach the basic fluctuation equilibrium does not depend on the infection probability and the level of the fluctuation remain unchanged even for long runs (d). Plots (e) and (f) show that with the same value of the infection probability, increasing the density of contacts produces larger fluctuations, a quicker convergence of the cost ($K = 30$ for plot (e) with respect to $K = 5$ for all others). The two scenarios have different oblivion ($r_\alpha = 10^{-3}$ (e), $r_\alpha = 10^{-4}$ (f)). Then, increasing p , the frequency of the oscillations remains the same but the peaks broaden.

6 Discussion and Conclusions

In this paper we have been modeled the cognitive mechanisms known as availability and representativeness heuristics. The role of the first one in the human decision making process seems to be to produce a probability estimation of an event based on the relative observed (registered) frequency distribution. The second heuristic, representativeness, acts inferring certain attributes from others easier-to-detect. Both heuristics are liable or "noise affected", but surely they represent a very fast way to analyze environmental data using little quantity of memory and time. But the very interesting aspect, and not underlined enough in literature, is the role of the cooperation between heuristics. The co-occurrence of their activities could be coordinate also in the human cognition, but of course it is very interesting from a computational point of view.

We supposed that the availability heuristic corresponds to a mean field estimation of the "risk", while representativeness partially maintains the memory

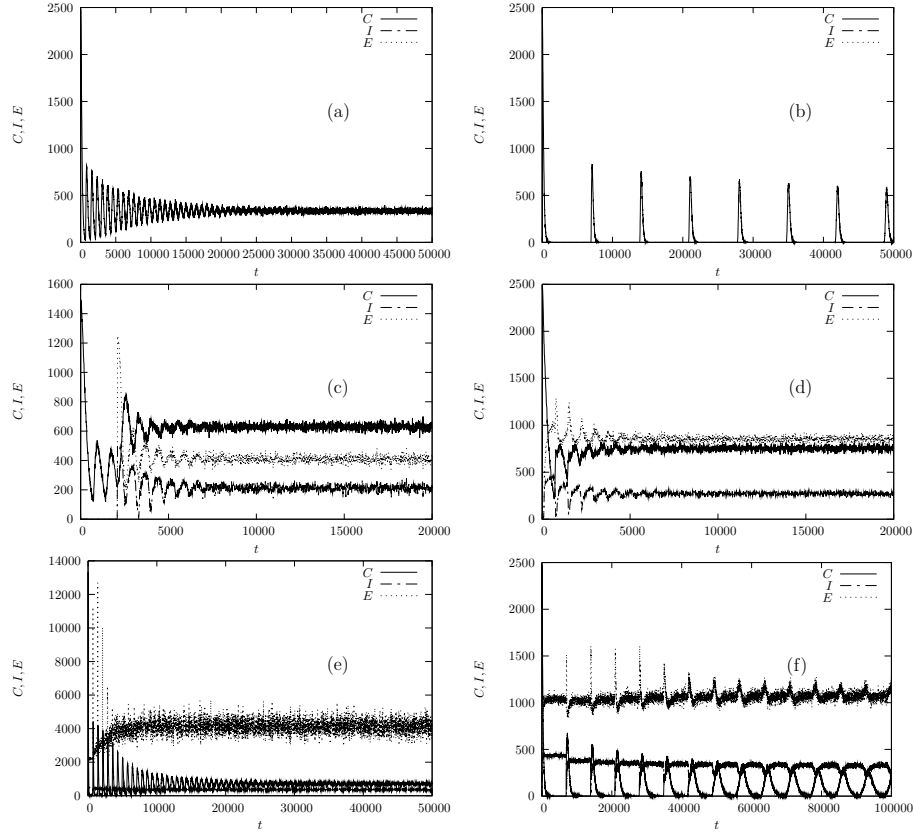


Fig. 5. Cost C , Infection level I and Errors E vs. time t for two different values of the parameter r_α , $r_\alpha = 10^{-3}$ (a,c,d,e); $r_\alpha = 10^{-4}$ (b,f), different values of p , $p = 0$, (a,b); $p = 10^{-2}$ (d,e,f); $p = 10^{-6}$, (c) and for some value of the connectivity ($K = 5$ for plots (a,b,c,d,f), $K = 30$ for plot (e)) and population $N = 500$.

of the previous interactions with the others. In the quenched and annealed scenarios we can capture the effect of the heuristics coordination. The quenched scenario considers the case of “systematic spreaders” where same agents emits at each time step a tainted message. In this case the availability heuristic would fails to minimize cost and infection if representativeness was absent.

On the contrary in the annealed scenario the spreaders are completely chosen at random at each time step. In this extreme case there is no information contained in the previous history of the system, and representativeness heuristic became completely useless. In this situation the only available information is the rate of infection, and availability heuristic is the most efficient way to minimize both cost and risk of infection.

The oblivion mechanism associated to the two heuristics determines both the cost of the control process and a sort of its reactivity. In average the cost, which represents the number of operations/computation to cope the task, is proportional to the oblivion value, the number of infected and errors are inversely proportional to the oblivion. If the cost as so as it happens in the biological domain, is considered as a quantity which the system has to minimized, it means that will exist an optimal value of both oblivion parameters for each possible condition. The reactivity of the control process could be defined as the time needed from the system to reduce to zero a new infection. In our model the oblivion of both the two heuristics appears to control also the size of “cost oscillations”. We found that the larger the oblivion level, the lower the oscillations and the time needed to reach the asymptotic equilibrium.

Our simulations show that under the infection, the cost reaches its asymptotic value much earlier than without infection. This suggests that a low value of infection level may even provide some advantages for the quick dumping of the oscillatory behavior resulting in an improved cost predictability.

The investigation of heuristics exploits a major overlap between artificial intelligence (AI), cognitive science and psychology. The interest in heuristics is based on the assumption that humans process information in ways that computers can emulate and heuristics may provide the basic bricks for bridging from brains to computers . Our model framework approach is quite general and offers some points of reflections on how the study of complex systems may become help developing new areas of AI. In the past years the AI community has debated as to whether the mind is best viewed as a network of neurons (connectionism), or as a collection of higher-level structures such as symbols, schemata, heuristics, and rules, *i.e.*, emphasizing the role of symbolic computation. Nowadays the symbolic representations to produce general intelligence is in slightly decline but the “neuron ensemble” paradigm has also shifted towards more complex models particularly taking into account and combining findings from both fNMR and cognitive psychology fields ([19,20]).

Here we show that the incorporation of simple heuristics in a small network of agents leads to a rich and complex dynamics. Our model does not take into account mutation and natural selection which is of key importance for the emer-

gence of complex behavior in animal societies and in the brain development (see for example Pinker and the follow up debate [21]).

A multi-agent model, where each agent represent a message/modifying person/neuron, can serve as a very natural abstraction of communication networks, and hence be easily used by psychologists as well as computer scientists. Such a model also allows the tracking of single agent fates so that communities with low member numbers are easily dealt with and these models also provide for much more detailed analysis compared to average population approaches like continuous differential equations.

Heuristics may have even greater value in case of environmental challenges, i.e. organisms need to adapt quickly to environmental fluctuations, for example starvation and high competition, they must be able to make inferences that are fast, frugal, and accurate. These real-world requirements lead to a new conception of what proper reasoning is: ecological rationality. Fast and frugal heuristics that are matched to particular environmental structures allow organisms to be ecologically rational. The study of ecological rationality thus involves analyzing the structure of environments, the structure of heuristics, and the match between them.

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